# When One LLM Drools, Multi-LLM Collaboration Rules

Shangbin Feng <sup>1</sup> Wenxuan Ding <sup>2</sup> Alisa Liu <sup>1</sup> Zifeng Wang <sup>3</sup> Weijia Shi <sup>1</sup> Yike Wang <sup>1</sup> Shannon Zejiang Shen <sup>4</sup> Xiaochuang Han <sup>1</sup> Hunter Lang <sup>4</sup> Chen-Yu Lee <sup>3</sup> Tomas Pfister <sup>3</sup> Yejin Choi <sup>5</sup> Yulia Tsvetkov <sup>1</sup>

# **Abstract**

This position paper argues that in many realistic (i.e., complex, contextualized, subjective) scenarios, one LLM is not enough to produce a reliable output. We challenge the status quo of relying solely on a single general-purpose LLM and argue for multi-LLM collaboration to better represent the extensive diversity of data, skills, and people. We first posit that a single LLM underrepresents real-world data distributions, heterogeneous skills, and pluralistic populations, and that such representation gaps cannot be trivially patched by further training a single LLM. We then organize existing multi-LLM collaboration methods into a hierarchy, based on the level of access and information exchange, ranging from API-level, textlevel, logit-level, to weight-level collaboration. Based on these methods, we highlight how multi-LLM collaboration addresses challenges that a single LLM struggles with, such as reliability, democratization, and pluralism. Finally, we identify the limitations of existing multi-LLM methods and motivate future work. We envision multi-LLM collaboration as an essential path toward compositional intelligence and collaborative AI development.

# 1. Introduction

The successes of scaling models (Kaplan et al., 2020) and data (Hoffmann et al., 2022) have fueled the overly optimistic hope that simply building an ever-larger language model is a path to achieving human-like intelligent AI models. From research artifacts to user-facing products, the commercialization of LLM and AI technologies further reinforces this status quo: major players train a single general-purpose in-house LLM and compete by attempting to out-

Preprint.

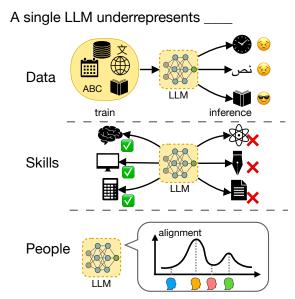


Figure 1. Despite the quest for general-purpose models, a single LLM suffers from underrepresentation of data (language varieties, domains, styles), skills (reasoning abilities, linguistic and communication skills, creative capacities, and technical competencies), and people (opinions, values, cultural norms).

rank other models (Henshall, 2024). This quest for the "best" single LLM—measured by leaderboard scores, user adoption, and profitability—has brought about the bloom of LLM research and development where new models emerge daily and the state-of-the-art is constantly reshaped (Liang et al., 2023a; Chiang et al., 2024b; Guo et al., 2025).

In this position paper, we challenge the status quo by arguing that **one LLM is not enough** and advocate for **multi-LLM collaboration**, where multiple language models collaborate for compositional generative modeling. We first argue *why* one LLM is not enough (§2): despite being general-purpose, a single monolithic model struggles to reflect the intricate diversity of the real world and *underrepresents* the long tail of data types, model skills, and people. We then propose a taxonomy of multi-LLM collaboration protocols (§3) in which LLMs collaborate, interact, and exchange information at the API-level, text-level, logit-level, and weight-level, offering diverse modes of collaboration compatible with all stages of the LLM lifecycle and usage types. We then argue that

<sup>&</sup>lt;sup>1</sup>University of Washington <sup>2</sup>The University of Texas at Austin <sup>3</sup>Google <sup>4</sup>Massachusetts Institute of Technology <sup>5</sup>Stanford University. Correspondence to: Shangbin Feng <shangbin@cs.washington.edu>.

multi-LLM systems empowered by these protocols bring out benefits that a single LLM struggles to reflect (§4): pluralism, democratization, efficiency, adaptability, and more. Together, these arguments demonstrate that multi-LLM collaboration is an important yet overlooked family of methods, and a promising approach to advance language technologies.

We also identify some limitations of existing multi-LLM collaboration protocols and applications (§5), which motivate us to lay out an actionable roadmap for future work beyond monolithic models and towards advancing modular multi-LLM systems. We hope that this position will be a call-to-action for the research community to propose, evaluate, and promote collaboration strategies and communication protocols for multi-LLM collaboration.

# 2. One LLM Is Not Enough

From the early successes of scaling up model size (Kaplan et al., 2020) and training data (Hoffmann et al., 2022), language technologies have transitioned from task-specific systems to "general-purpose" language models (Brown et al., 2020): by pretraining on gigantic corpora and aligning with extensive instruction tuning and preference optimization, one LLM can be prompted to solve a diverse range of tasks and problems, leading some to believe that the future of language technologies is in figuring out the recipe for scaling and developing a single omnipotent LLM. Despite its promise, we argue that a single LLM, as designed today, is not enough to achieve a truly reliable system: even with the best effort to curate data, design architectures, and improve model inference, a single LLM suffers from *underrepresentation* on three fronts: data, skills, and people.

Underrepresentation of data. Despite extensive data curation efforts, a single LLM is ultimately trained on a static snapshot of what is readily available, and there are always elements in the real-world language distributions that are missing or down-weighted in this static snapshot (Lazaridou et al., 2021). For example, constant changes in the state of the world after the time of data collection quickly make the parametric information of LLMs outdated (Dhingra et al., 2022; Kasai et al., 2024). Private and copyrighted texts would require careful consideration in LLM training, but are otherwise essential for personalization and context (Wei et al., 2024; Chen et al., 2024). Languages, dialects, language varieties in the long tail of data distributions are easily outnumbered and overshadowed by the majority languages/dialects (Song et al., 2023; Faisal et al., 2024). Evolving trends, unspoken cultural and social norms essential for socially-aware LLM applications, commonsense and implicit knowledge are hard to pin down with static data snapshots (Rao et al., 2024; Shi et al., 2024c). The list goes on, and much of the real-world variation expressed through

language will inevitably be lost when we solely rely on a single LLM with a static hodgepodge of training corpora.

**Underrepresentation of skills.** Earlier language technologies were defined by task-specific progress with specialized methods, models, and subcommunities of experts for tasks like machine translation, summarization, question answering, and natural language inference (Sun et al., 2022). LLMs broke from this trend by being seemingly "general-purpose" and it appears plausible that all we will need in the near future is a single omnipotent LLM that works best in any task and context.

However, no single LLM is Pareto-optimal empirically and it is prohibitively expensive (if not impossible) to optimize for a single model that outperforms all other models on all skills. For example, Gemini (Team et al., 2023) currently ranks best on Chatbot Arena (Chiang et al., 2024b) focusing on instruction following, GPT-40 (Achiam et al., 2023) is best on the HELM leaderboard (Liang et al., 2023a) with an emphasis on OA and math reasoning, while a fine-tuned version of InternLM (Team, 2023) is best on textual and algorithmic tasks in Big-Bench Hard (Suzgun et al., 2023) on Open LLM Leaderboard (Fourrier et al., 2024). These models would all rankly poorly on GlobalBench (Song et al., 2023) and DialectBench (Faisal et al., 2024) compared to multilingual LLMs, where tasks include languages and language varieties not captured in the most popular leaderboards. This demonstrates that even the most advanced LLMs have major limitations in skills and task coverage, and that additional specialization of models is critical.

**Underrepresentation of people.** All LLMs are ultimately used by people with diverse needs, pluralistic values, and varying socio-cultural backgrounds. Despite the everincreasing model size and benchmark scores, we witness a constant lack of representation of actual LLM users.

On one hand, a single LLM struggles to reflect pluralistic human values, cultures, and social contexts (Sorensen et al., 2024b; Feng et al., 2024d; Leibo et al., 2024), in any language. LLM users are not homogeneous, bringing a wealth of perspectives and diversity that reflects and shapes our world: despite the potential diversity in data sources, even state-of-the-art LLMs cannot equitably serve the entire spectrum of users by reflecting such heterogeneity. For example, LLMs often feature a West-centric cultural persona (Naous et al., 2023) and struggle to adapt to cultural variation (Rao et al., 2024); a single LLM would most likely reinforce the majority class in training data and exhibit biases in opinions and perspectives (Santurkar et al., 2023; Feng et al., 2023a); user agency often remains overlooked since monolithic LLMs lack steerability and controllability

<sup>&</sup>lt;sup>1</sup>Leaderboards accessed on Nov 24, 2024.

in value-laden instructions and contexts (Sorensen et al., 2024a). Since LLMs are already trained on diverse texts from the web, representing populations would require solutions beyond scaling data for a general-purpose LLM.

Moreover, by solely relying on one single model we are also solely relying on only one team of model developers. With the increasing cost and opaqueness of independently developing an LLM, these teams are becoming highly homogeneous: big tech companies, researchers with advanced degrees, overrepresentation of certain demographic groups are common sketches of the teams behind state-of-the-art LLMs (EEOC, 2024). However, this leaves the vast majority of actual and underprivileged LLM users without a say in the decision making of model training and development, while they can only access these LLMs which might not have been developed with their needs and priorities in mind. An open and collaborative development approach that is the cornerstone of open-source communities (Johnson, 2006) is thus neglected in the over-focus on chasing the best single model, underrepresenting the voices and needs of actual LLM users that go beyond synthetic benchmark numbers.

Challenges to Improve One Model's Coverage A tempting solution to these problems of underrepresentation is to further train the current best LLM to improve the representation of data, skills, and users. We argue that this band-aid approach is challenging at best:

When *data* is underrepresented, model developers can scrape from previously unseen domains and perform further fine-tuning. However, it is costly to frequently re-train and update model versions with gigantic LLMs, while private and copyrighted data simply should not be included in LLM training data. Retrieval-augmented geneartion (Guu et al., 2020; Shi et al., 2023) could provide unseen data as context, but it is unclear whether LLMs would fully leverage the context (Shi et al., 2024b) and to what extent is this steerability reliable (Sprague et al., 2024).

When *skills* are underrepresented, model developers can derive targeted supervised fine-tuning data for continual learning (Zhang et al., 2023). However, tuning to patch a weakness in skills may lead to tradeoffs in other tasks and sometimes even catastrophic forgetting (Luo et al., 2023; Lin et al., 2024), as any specialization on the trained model might harm its general-purpose utility.

When *humans* are underrepresented, model developers can survey the needs of diverse populations and communities for LLMs and invite collaborative contributions (Feng et al., 2024a). However, there is little to no incentive for teams behind commercial state-of-the-art LLMs to take great strides towards equitable language technologies without obvious profitable gains.

It is important to note that these underrepresentation issues of a single LLM, especially with respect to data and skills, are grounded in *empirical evidence*, i.e., current state-of-the-art LLMs are suffering from these challenges. There might emerge future "perfect" algorithms/architectures/etc. that fully address these issues, but given that multi-LLM collaboration research is *already demonstrating empirical benefits* in addressing these issues, we advocate for multi-LLM collaboration as a promising and effective research avenue.

# 3. Types of Multi-LLM Collaboration

We categorize existing (often unrelated) method into a conceptual family of multi-LLM collaboration strategies, organizing the methods by (1) collaboration at different levels of access to an LLM, as illustrated in Figure 2, and (2) collaboration at different stages of LLM's lifecycle: (pre)training, post-training, and inference.

#### 3.1. Collaboration at different levels of model access

**API-Level** As the name suggests, access to an LLM's API is sufficient to enable API-level collaboration between models. Such strategies focus on the dynamic selection of the most cost-efficient and high-performing model among a diverse pool of LLMs for different inputs. Intuitively, we should assign simpler requests to smaller (Tambon et al., 2024), more efficient LLMs for *reduced cost and latency*, and domain-specific requests to expert LLMs for *improved performance*. There are two mainstream lines of research on API-level LLM collaboration: *Routing* (Hu et al., 2024) and *Cascading* (Chen et al., 2023).

Routing selects the most suitable model only based on the input, without performing inference on any LLM. A typical routing paradigm involves designing a separate router model that learns from human preferences. As a key step, preference labels (Ong et al., 2024) that represent the relative response quality of different LLMs are collected for each input. Prior work developed various router models to learn from input-preference pairs, including non-parametric routers like KNN-based router (Shnitzer et al., 2023), and parametric routers like MLP- (Hu et al., 2024), encoder-(Ding et al., 2024), and decoder-based (Ong et al., 2024) routers. Beyond preference data, additional information can be leveraged to assist in routing decision-making. To select the most suitable expert LLM, domain-specific routing strategies Lu et al. (2023); Stripelis et al. (2024) extract key information about the task and domain directly from the input. Feng et al. (2024f) further introduce a heterogeneous graph framework to leverage contextual interactions among tasks, queries, and LLMs.

Cascading defers the input to larger/more capable LLMs when the response from the smaller LLM is not satisfac-

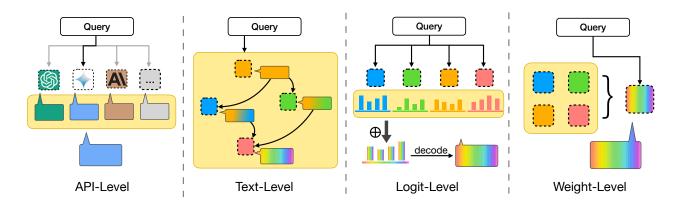


Figure 2. We propose a typology of multi-LLM collaboration approaches, focusing on different levels of access to LLMs, and survey existing methods that fall into each type.

tory enough. The crux of cascading is the *deferral rule* to determine whether to terminate and return the prediction or to invoke the next LLM. The pioneering work Frugal GPT (Chen et al., 2023) trains a regression model that predicts a response quality score and establishes the deferral rule by thresholding the predicted score. Yue et al. (2023) presents a consistency-based approach that estimates the response confidence score, such that inputs with low response confidence are deferred to the next LLM. Gupta et al. (2024) further incorporate token-level uncertainty into deferral rules. Cascading strategies, while potentially improving overall quality by leveraging additional signal from smaller LLMs, often come with increased cost and latency due to the overhead of decoding intermediate responses.

**Text-Level** Text-level approaches enable multi-LLM collaboration through exchanges of generated texts, where one LLM's output becomes another LLM's input. They usually follow a conversational setting where LLMs can "cooperate" or "compete" with each other.

For cooperation, models can *divide and conquer* complex problems through multi-agent systems where each agent is seeded by different models/prompts (Wu et al., 2024a; Guo et al., 2024); specialized models can *augment* general-purpose LLMs to patch their gaps (Feng et al., 2024a; Shen et al., 2024); one LLM can generate *feedback* or perform verification for another LLM's outputs and consequently refine the generation (Burns et al., 2024; Feng et al., 2024b).

For *competition*, multiple LLMs can "debate" with each other to advance factuality and reasoning (Liang et al., 2023b; Du et al., 2024a). Recent research also explored employing a pool of diverse specialized LLMs to model social (Zhao et al., 2024a) and economic (Zhao et al., 2024b) behavior to simulate the real-world environment.

Much effort of multi-LLM collaboration research currently

operates at the text-level, probably because such interaction allows for the use of APIs in closed models, the ease of engineering to redirect model outputs, and transparency through intermediate model outputs. However, text-level multi-LLM collaboration also faces challenges such as error propagation from outputs of individual models, the lack of generalization across tasks, and the costs of model inference for multiple LLMs.

**Logit-Level** LLMs may also collaborate by jointly contributing to each next-token prediction. In this case, the logit-level predictions of multiple LLMs are combined via arithmetics to create a single next-token logit distribution, which is then normalized into a probability distribution. This approach uses other LLMs as "experts" and/or "anti-experts", whose predictions are additively or negatively combined in the prediction, respectively.

Using an anti-expert achieves the effect of steering *away* from the preferences of that model, and is also known as *contrastive decoding* (Li et al., 2023). For instance, the anti-expert may be an LLM tuned explicitly to be toxic (Liu et al., 2021), to achieve safer generations, or a smaller LLM (Li et al., 2023), to avoid the pitfalls of weaker LMs for better open-ended generation. In fact, the anti-expert does not need to be a distinct LLM, and can instead be the result of ablating some part of the current LLM, e.g., by withholding necessary context (Pei et al., 2023; Sennrich et al., 2024; Leng et al., 2024; Shi et al., 2024b) or early-exiting from an earlier layer of the transformer model (Gera et al., 2023; Chuang et al., 2024).

On the other hand, using multiple expert LLMs combines their predictions in a product-of-experts fashion. Intuitively, this leads to next-token predictions that are high-probability under all LLMs. This has been used to achieve decodingtime adaptation of LLMs using small tuned experts with a large pretrained LLM (Liu et al., 2024; Mitchell et al., 2024), allowing for on-the-fly customization of the weights of multiple finetuning objectives (Shi et al., 2024a).

The weights assigned to experts and anti-experts may also be automatically determined at each time step (Mavromatis et al., 2024; Fan et al., 2024; Du et al., 2024b). At the extreme, this takes the form of token-level routing among models (Shen et al., 2024).

Weight-Level The collaboration of multiple LLMs through parameter-level collaboration has been explored using paradigms such as mixtures of feed-forward layers (Sukhbaatar et al., 2024), adapters (Wang et al., 2022b; Pfeiffer et al., 2020), and low-rank adaptation (LoRA) experts (Wu et al., 2024b). In this paradigm, components like feed-forward layers and adapters are first trained independently on domain-specific or task-specific data to achieve specialization. Subsequently, in a combination stage, these independently trained modules are jointly optimized to collaborate effectively, creating a unified system that benefits from the specialized expertise of each component.

This framework supports collaboration across varying levels of input granularity the way experts are selected and aggregated. For example, some approaches dynamically select modules for individual *tokens* (Vaswani, 2017; Houlsby et al., 2019; Pfeiffer et al., 2020; Belofsky, 2023; Wu et al., 2024b; Sukhbaatar et al., 2024), enabling fine-grained expertise sharing. Others perform collaboration at the *sentence* level (Diao et al., 2023; Xu et al., 2023), where different input sentences activate different modules. At the *task* level, methods such as Chiang et al. (2024a) assign a single expert model to all examples from a particular task. Weight-level collaboration typically allows for deeper integration of experts by enabling routing decisions at each layer where modules are inserted, offering greater flexibility and adaptability to diverse tasks and data.

Another line of weight-level collaboration research is the merging/composition of model weights across multiple LLMs. These approaches mainly vary by data dependency, i.e., how much task-specific data is required to compose and adapt models. Zero-shot model composition approaches rely on heuristics about model weights (Yu et al., 2024; Yadav et al., 2024b) or task arithmetic (Ilharco et al., 2023) to produce composed models and advance generalization without access to task data. Given a small set of task data, dynamic composition approaches optimize the model composition based on performance and metrics on the task data (Huang et al., 2023) with perplexity heuristics (Mavromatis et al., 2024) and evolutionary algorithms (Feng et al., 2024e). If supervised data is abundant, learn-to-fuse approaches design trainable modules (Bansal et al., 2024), adapters (Wang et al., 2024), or even LLMs (Jiang et al., 2023a) to "glue"

multiple LLMs together: the component LLMs are often kept frozen while the trainable parts go through supervised fine-tuning from scratch. Weight-level approaches offer a spectrum of solutions based on data availability, and the *many-to-one* setup offers reduced inference costs. However, weight-level approaches are less interpretable in how model expertise is composed and do not tap into the power of collaborative generation like text- or logit-level approaches.

# 3.2. Collaboration at different stages of LLM development

We can also categorize multi-LLM collaboration approaches by the three stages of the LLM lifecycle: (pre)training, posttraining, and inference. Pretraining-time approaches focus on partitioning LLM training data (Gururangan et al., 2023) and training multiple specialized LLMs separately (Li et al., 2022) or at the same time (Devvrit et al., 2024). Post-training approaches explore collaborative alignment with modular reward models (Jang et al., 2023), multi-LLM self-alignment (Feng et al., 2024d), or constructing synthetic supervised fine-tuning data through multi-LLM debate (Subramaniam et al., 2024; 2025). The vast majority of multi-LLM collaboration approaches currently operate at inference time, offering diverse ways of reusing existing models spanning all four collaboration levels (Hu et al., 2024; Du et al., 2024a; Liu et al., 2024). In general, weightlevel methods often require more (pre)training and posttraining efforts, while API-level/logit-level collaborations focus more on inference-time solutions.

By conceptually structuring and organizing these (originally unrelated) methods into a family of approaches, we argue that multi-LLM collaboration research offers flexible methodologies for any level of model access across all stages in the LLM lifecycle, providing an alternative and promising school of thought to advance language technologies.

#### 4. The Promise of Multi-LLM Collaboration

Multi-LLM collaboration systems offer unique advantages over single general-purpose models: we summarize the methodological and empirical benefits of existing multi-LLM proposals in this section.

**Factuality and reliability** Despite prior efforts (Shi et al., 2023; Press et al., 2022; Feng et al., 2023b) to expand the knowledge of LLMs, knowledge gaps—missing or outdated information in LLMs—may persist due to the ever-evolving nature of knowledge, presenting challenges to the reliability of LLM responses. Self-reflection (Wang et al., 2022a; Xu et al., 2024; Shinn et al., 2024; Madaan et al., 2024), where a single LLM critically evaluates its own generations, is

used in decoding, confidence calibration, and inference to improve factual accuracy and mitigate hallucinations. However, this method suffers from confirmation biases (Ji et al., 2023) and relies on the assumption that LLMs can generate novel reflections from their initial outputs (Liang et al., 2023b). Recent studies address these issues by promoting collaboration between multiple LLMs. With distinct knowledge gaps, LLMs evaluate and reflect on each other's outputs, collaboratively probing and identifying the knowledge gaps of each other. Specifically, Feng et al. (2024c) enable robust LLM abstention through multi-LLM collaboration to reflect on generated text in cooperative or competitive settings. Cohen et al. (2023) employ cross-examination to detect errors in LLM generations. Other studies (Xiong et al., 2023; Liang et al., 2023b; Du et al., 2024a) suggest that multiple LLMs could propose and debate their individual responses and reasoning processes over multiple rounds to arrive at a common final answer, and LLMs with comparable abilities have been shown to demonstrate such collaborative spirit (Xiong et al., 2023). Given its superior performance in various experiment settings, we believe that multi-LLM collaboration offers a promising way to further improve the factual validity of generated context and reduce fallacious answers and hallucinations that contemporary models are prone to.

**Alignment and pluralism** State-of-the-art LLMs are documented with all kinds of cultural (Naous et al., 2023), political (Santurkar et al., 2023), and broadly social biases (Kumar et al., 2023). This comes with the fact that these models have already seen "diverse" web data that should serve as a decentralized representation of real-world diversity. Much research attributes this to LLMs learning disproportionately from and hence reinforcing the majority in training data (Feng et al., 2023a; Gallegos et al., 2024), thus scaling data diversity used in training a single LLM is not an effective solution. We see an increasing line of work focused on modular multi-LLM systems to alleviate these biases, including modular plug-ins (Feng et al., 2024d), multi-LLM as a judge (Zhao et al., 2024a), and employing multiple and compositional reward models (Jang et al., 2023). Together with data-side modularity spanning diverse communities (Kumar et al., 2024; Kirk et al., 2024) we believe multi-LLM collaboration offers a modular and flexible solution to addressing the fairness and pluralism challenges of LLMs.

**Efficiency** The most capable LLMs at the moment often feature gargantuan sizes and prohibitively high inference costs. However, not all queries require such computation overhead: by employing multi-LLM collaboration across sizes/expertise the largest model doesn't need to be called every single time. MatFormer (Devvrit et al., 2024) simultaneously trains modules of varying sizes in a nested architecture and could be selectively activated to result in

LLMs of varying sizes given the compute budget. Instead of training an LLM on *all* the data, approaches such as Branch-Train-Merge (Li et al., 2022) leverage the modularity of data provenance to train a pool of LLM experts and dynamically aggregated for inference. A growing line of research also investigates *defer* and *backoff* behavior between models of varying sizes and/or specialization (Shen et al., 2024; Jung et al., 2024). These approaches highlight multi-LLM collaboration as a promising direction to balance utility and training/inference efficiency.

**Adaptation** Training a gigantic LLM and re-purposing it with prompt engineering is the most popular status quo of LLM research and applications. However, one gigantic model is prohibitively expensive to re-train and update, while the effectiveness of prompt-based adaptation is limited and brittle (Sprague et al., 2024). Multi-LLM collaboration offers strategies for adapting language models that are lightweight and flexible: Token-level methods pair a general-purpose LLM with specialized peers for collaborative generation (Shen et al., 2024); logit-level approaches mixes the logit distributions of multiple LLMs for collaborative decoding (Liu et al., 2024); weight-level approaches flexibly reuse and adapt existing models/adapters through weight arithmetic (Ilharco et al., 2023; Han et al., 2023; Yadav et al., 2024b; Feng et al., 2024e). Multi-LLM collaboration offers diverse and flexible solutions for adaptation spanning varying levels of model access.

Privacy Despite the extensive effort to curate (pre)training data, private and copyrighted data will need to be left out for privacy, compliance, and ethics concerns (Karamolegkou et al., 2023; Yao et al., 2024). These data sets are nonetheless helpful in highly specialized or personalized contexts. Multi-LLM offers preliminary solutions where private/copyrighted data could be employed in a local model at the data provenance, then interact with a larger general-purpose model (Zhang et al., 2024). Though it might be possible to extract private data from the model (Carlini et al., 2021), we envision future work on augmenting the "private" LLM with contextual integrity guardrails (Mireshghallah et al., 2024) for controllable and context-aware information sharing.

Democratization and collaborative development A single LLM is often trained by only a team of researchers and engineers, struggling to reflect the diversity of real-world LLM users. The priorities of long-tail and underprivileged users are often not incorporated when making decisions about model training and alignment. On the contrary, multi-LLM collaboration uniquely enables decentralized and collaborative development: all stakeholders in LLM development and applications could contribute models based on their needs, priorities, and compute budgets, then composed

through various levels of multi-LLM collaboration protocols (§3). In this way, we democratize language technologies through participatory and collaborative development where everyone is welcome.

# 5. Future Directions for Multi-LLM Collaboration Research

We identify various limitations of existing multi-LLM collaboration systems and motivate future work.

Theories of human communication While the current approach focuses on developing a single general-purpose LLM, there is no "general-purpose" human, but specialized individuals collaborating through various communication protocols for collective intelligence (Hutchins, 2000). We thus argue that future multi-LLM collaboration research could benefit from cognitive science and communications theories, designing social science-inspired protocols for multiple LLMs to compose and collaborate.

**Encapsulation and handoff** Another interesting challenge in multi-LLM collaboration is the absence of clear handoff boundaries. In software engineering, encapsulation serves as a cornerstone of collaborative development by establishing well-defined interfaces between components: modifications to one part of the codebase do not propagate unexpected changes to others. However, especially in weight-level LLM collaboration, cleanly separating and containing the expertise of different models remains an open challenge. While recent work has demonstrated progress in developing modularized model components (Pfeiffer et al., 2020; Hu et al., 2021; Yadav et al., 2024a), modifications to base model weights can still introduce unpredictable behavioral changes beyond the intended training objectives (for example, catastrophic forgetting (McCloskey & Cohen, 1989; Kirkpatrick et al., 2017)). Developing reliable encapsulation mechanisms can ensure robust and predictable model composition, and could be a critical step to achieve the vision for "building LMs like open-source software" (Raffel, 2021).

Compatibility with the status quo Despite the active research in multi-LLM collaboration, there is limited uptake in large-scale and industry settings beyond academic papers. One reason could be that many existing multi-LLM approaches require the training/development of extra modules such as gates and routers (Jiang et al., 2023a; Muqeeth et al., 2024), while most open-source activities only feature the sharing of model weights. We thus argue that future multi-LLM protocols should be compatible with the status quo of model sharing by employing limited to no extra step beyond employing existing model checkpoints.

Interpretability insights Interpretability techniques unveil the mechanisms underlying language models for reasoning (Stolfo et al., 2023), factual association (Meng et al., 2022), and more (Nanda et al., 2023). The interpretability insights enable localized manipulation of sub-modules for efficient enhancement and editing (Yin et al., 2024), thereby facilitating the potential for lightweight multi-model collaboration. Moreover, while diverse language models may exhibit similar or distinct mechanisms for comparable tasks, the reliability of their capability beyond mere memorization varies (Yang et al., 2024). Interpretability tools offer insights into determining the fitting weight/contribution of each component model in multi-LLM collaboration and could lead to improved collaboration outcomes.

Evaluating multi-LLM collaboration Research on modular and multi-LLM systems has not yet devised an agreed-upon and detailed evaluation methodology. Most of the existing work resorts to evaluation with tasks and datasets typical for a single LLM. Future work could explore specifically evaluating multi-LLM collaboration, designing tasks and datasets where multiple models are evaluated separately and in collaboration, e.g., ablating by withholding copyright data (Min et al., 2024), or evaluating multi-agent collaboration where multiple models divide and conquer complex problems (Guo et al., 2024).

**Democratizing ways of contribution** While we hope that collaborative and participatory contributions to multi-LLM systems could alleviate the underrepresentation of people, not everyone knows how to train an LLM and contribute. This is especially true for the already underrepresented and underprivileged (Kirk et al., 2024), thus the benefits of multi-LLM collaboration will not reach them if we expect users to train and contribute models on their own. Thus, we argue that we should lower the barrier of contribution: for example, by designing an agent framework that automatically solicits user feedback in natural language, fetches data, trains models, generates synthetic data to evaluate, and finally pushes the model and contribute. In this way, users only need to provide a few sentences of feedback about the gaps in existing LLMs, and a new component LLM could be developed and contributed on their behalf.

#### 6. Alternative Views

We identify two alternative views to our position.

We could patch the underrepresentations of data, skills, and people by further augmenting a single model. While existing band-aid approaches such as LoRA fine-tuning (Hu et al., 2021) or retrieval augmented generation (RAG) (Shi et al., 2023; Jiang et al., 2023b; Asai et al., 2024) patch the gaps in data and skills to some extent, we present em-

pirical evidence of their limitations in Section 2, suffering from challenges such as privacy and copyright, catastrophic forgetting, lack of participation, and more. Further fine-tuning with LoRA could patch the gap of skills, but it risks jeopardizing the general-purposeness and leads to tradeoffs of existing skills (Kirkpatrick et al., 2017); retrieval could provide new information and data to improve reliability, but there is no guarantee that LLMs would fully leverage the retrieved context (Shi et al., 2024b). While it is not impossible that with future progress a single LLM could offer perfect representations, we argue that multi-LLM collaboration offers a more concrete and actionable roadmap to advance language technologies, and a more efficient one, as it reuses developments made so far.

We could enable collaboration through a single model. It is theoretically possible to collaborate in the development lifecycle of a single model. Different communities could contribute heterogeneous data to be combined for training a single model; different engineering teams could train part of the model architecture for later merging; different users could annotate diverse alignment preferences to jointly align an LLM. We argue that while they are all possible, it is more natural to collaborate on the level of models since 1) model sharing is the default open-source activity, 2) there are already 1,261,059 LLMs<sup>2</sup> openly available for collaboration, and 3) the companies that have the resource to carry out these protocols are incentivized to not go open about development of their LLM for competitive advantage. We envision multi-LLM collaboration as a promising path to reuse existing models, promote collaborative development, and advance compositional intelligence.

#### 7. Related Work

Two recent works discuss related topics.

Yadav et al. (2024a) present a taxonomy of model merging and mixture-of-experts (MoE) approaches, arguing for reusing and routing of existing expert models. They focus primarily on weight-level collaboration approaches, while we aggregate a broader family of methods with a broader definition of *multi-LLM collaboration* where models could collaborate through four different levels of information exchange.

Du & Kaelbling (2024) present a position paper arguing for compositional generative modeling, discussing the benefits of combining multiple modules across computer vision, reinforcement learning, robotics, and a brief mention of language. We specifically focus on language models and dive deep into LLM-specific arguments, methods, and future research.

#### 8. Conclusion

We argue that one LLM is not enough and advocate for multi-LLM collaboration to better represent diverse data distributions, heterogeneous skills, and pluralistic populations. We propose a hierarchy of existing multi-LLM collaboration approaches based on information exchange levels, spanning API-level, text-level, logit-level, and weight-level collaboration. We then summarize the benefits of existing multi-LLM systems over a single model and discuss the limitations of existing methods to motivate future work. We envision multi-LLM collaboration as a viable path to compositional intelligence and an important initiative toward collaborative AI development.

#### References

Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Asai, A., Wu, Z., Wang, Y., Sil, A., and Hajishirzi, H. Selfrag: Learning to retrieve, generate, and critique through self-reflection. In *The Twelfth International Conference* on Learning Representations, 2024.

Bansal, R., Samanta, B., Dalmia, S., Gupta, N., Ganapathy, S., Bapna, A., Jain, P., and Talukdar, P. Llm augmented llms: Expanding capabilities through composition. In *The Twelfth International Conference on Learning Repre*sentations, 2024.

Belofsky, J. Token-level adaptation of lora adapters for downstream task generalization. In *Proceedings of the 2023 6th Artificial Intelligence and Cloud Computing Conference*, pp. 168–172, 2023.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., teusz Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., Mc-Candlish, S., Radford, A., Sutskever, I., and Amodei, D. Language models are few-shot learners. *ArXiv*, abs/2005.14165, 2020.

Burns, C., Izmailov, P., Kirchner, J. H., Baker, B., Gao, L., Aschenbrenner, L., Chen, Y., Ecoffet, A., Joglekar, M., Leike, J., et al. Weak-to-strong generalization: Eliciting strong capabilities with weak supervision. In *Forty-first International Conference on Machine Learning*, 2024.

Carlini, N., Tramer, F., Wallace, E., Jagielski, M., Herbert-Voss, A., Lee, K., Roberts, A., Brown, T., Song, D., Erlingsson, U., et al. Extracting training data from large

<sup>&</sup>lt;sup>2</sup>Huggingface accessed on Jan 6, 2025.

- language models. In *30th USENIX Security Symposium* (*USENIX Security 21*), pp. 2633–2650, 2021.
- Chen, L., Zaharia, M., and Zou, J. Frugalgpt: How to use large language models while reducing cost and improving performance. *arXiv preprint arXiv:2305.05176*, 2023.
- Chen, T., Asai, A., Mireshghallah, N., Min, S., Grimmelmann, J., Choi, Y., Hajishirzi, H., Zettlemoyer, L., and Koh, P. W. Copybench: Measuring literal and non-literal reproduction of copyright-protected text in language model generation. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 15134–15158, 2024.
- Chiang, W.-L., Zheng, L., Sheng, Y., Angelopoulos, A. N., Li, T., Li, D., Zhang, H., Zhu, B., Jordan, M., Gonzalez, J. E., et al. Chatbot arena: An open platform for evaluating llms by human preference. *arXiv* preprint *arXiv*:2403.04132, 2024a.
- Chiang, W.-L., Zheng, L., Sheng, Y., Angelopoulos, A. N., Li, T., Li, D., Zhu, B., Zhang, H., Jordan, M., Gonzalez, J. E., et al. Chatbot arena: An open platform for evaluating llms by human preference. In *Forty-first International Conference on Machine Learning*, 2024b.
- Chuang, Y.-S., Xie, Y., Luo, H., Kim, Y., Glass, J. R., and He, P. Dola: Decoding by contrasting layers improves factuality in large language models. In *The Twelfth Inter*national Conference on Learning Representations, 2024.
- Cohen, R., Hamri, M., Geva, M., and Globerson, A. Lm vs lm: Detecting factual errors via cross examination. *arXiv* preprint arXiv:2305.13281, 2023.
- Devvrit, F., Kudugunta, S., Kusupati, A., Dettmers, T., Chen, K., Dhillon, I. S., Tsvetkov, Y., Hajishirzi, H., Kakade, S. M., Farhadi, A., , and Jain, P. Matformer: Nested transformer for elastic inference. In *NeurIPS*, 2024.
- Dhingra, B., Cole, J. R., Eisenschlos, J. M., Gillick, D., Eisenstein, J., and Cohen, W. W. Time-aware language models as temporal knowledge bases. *Transactions of the Association for Computational Linguistics*, 10:257–273, 2022.
- Diao, S., Xu, T., Xu, R., Wang, J., and Zhang, T. Mixture-of-domain-adapters: Decoupling and injecting domain knowledge to pre-trained language models memories. *arXiv* preprint arXiv:2306.05406, 2023.
- Ding, D., Mallick, A., Wang, C., Sim, R., Mukherjee, S., Ruhle, V., Lakshmanan, L. V., and Awadallah, A. H. Hybrid llm: Cost-efficient and quality-aware query routing. *arXiv preprint arXiv:2404.14618*, 2024.

- Du, Y. and Kaelbling, L. P. Position: Compositional generative modeling: A single model is not all you need. In *Forty-first International Conference on Machine Learning*, 2024.
- Du, Y., Li, S., Torralba, A., Tenenbaum, J. B., and Mordatch, I. Improving factuality and reasoning in language models through multiagent debate. In *Forty-first International Conference on Machine Learning*, 2024a.
- Du, Y., Zhao, S., Zhao, D., Ma, M., Chen, Y., Huo, L., Yang, Q., Xu, D., and Qin, B. MoGU: A framework for enhancing safety of LLMs while preserving their usability. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024b.
- EEOC. High tech, low inclusion: Diversity in the high tech workforce and sector 2014 2022, 2024.
- Faisal, F., Ahia, O., Srivastava, A., Ahuja, K., Chiang, D., Tsvetkov, Y., and Anastasopoulos, A. DIALECTBENCH: An NLP benchmark for dialects, varieties, and closelyrelated languages. In Ku, L.-W., Martins, A., and Srikumar, V. (eds.), Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2024.
- Fan, C., Lu, Z., Wei, W., Tian, J., Qu, X., Chen, D., and Cheng, Y. On giant's shoulders: Effortless weak to strong by dynamic logits fusion. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.
- Feng, S., Park, C. Y., Liu, Y., and Tsvetkov, Y. From pretraining data to language models to downstream tasks: Tracking the trails of political biases leading to unfair nlp models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 11737–11762, 2023a.
- Feng, S., Shi, W., Bai, Y., Balachandran, V., He, T., and Tsvetkov, Y. Cook: Empowering general-purpose language models with modular and collaborative knowledge. *arXiv preprint arXiv:2305.09955*, 2023b.
- Feng, S., Shi, W., Bai, Y., Balachandran, V., He, T., and Tsvetkov, Y. Knowledge card: Filling llms' knowledge gaps with plug-in specialized language models. In *The Twelfth International Conference on Learning Representations*, 2024a.
- Feng, S., Shi, W., Wang, Y., Ding, W., Balachandran, V., and Tsvetkov, Y. Don't hallucinate, abstain: Identifying LLM knowledge gaps via multi-LLM collaboration. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, August 2024b.

- Feng, S., Shi, W., Wang, Y., Ding, W., Balachandran, V., and Tsvetkov, Y. Don't hallucinate, abstain: Identifying llm knowledge gaps via multi-llm collaboration. *arXiv* preprint arXiv:2402.00367, 2024c.
- Feng, S., Sorensen, T., Liu, Y., Fisher, J., Park, C. Y., Choi, Y., and Tsvetkov, Y. Modular pluralism: Pluralistic alignment via multi-llm collaboration. In *Proceedings of the* 2024 Conference on Empirical Methods in Natural Language Processing, pp. 4151–4171, 2024d.
- Feng, S., Wang, Z., Wang, Y., Ebrahimi, S., Palangi, H., Miculicich, L., Kulshrestha, A., Rauschmayr, N., Choi, Y., Tsvetkov, Y., et al. Model swarms: Collaborative search to adapt llm experts via swarm intelligence. *arXiv* preprint arXiv:2410.11163, 2024e.
- Feng, T., Shen, Y., and You, J. Graphrouter: A graph-based router for llm selections. *arXiv* preprint *arXiv*:2410.03834, 2024f.
- Fourrier, C., Habib, N., Lozovskaya, A., Szafer, K., and Wolf, T. Open llm leaderboard v2, 2024.
- Gallegos, I. O., Rossi, R. A., Barrow, J., Tanjim, M. M., Kim, S., Dernoncourt, F., Yu, T., Zhang, R., and Ahmed, N. K. Bias and fairness in large language models: A survey. *Computational Linguistics*, pp. 1–79, 2024.
- Gera, A., Friedman, R., Arviv, O., Gunasekara, C., Sznajder, B., Slonim, N., and Shnarch, E. The benefits of bad advice: Autocontrastive decoding across model layers. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2023.
- Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.
- Guo, T., Chen, X., Wang, Y., Chang, R., Pei, S., Chawla, N. V., Wiest, O., and Zhang, X. Large language model based multi-agents: A survey of progress and challenges. *arXiv* preprint arXiv:2402.01680, 2024.
- Gupta, N., Narasimhan, H., Jitkrittum, W., Rawat, A. S., Menon, A. K., and Kumar, S. Language model cascades: Token-level uncertainty and beyond. arXiv preprint arXiv:2404.10136, 2024.
- Gururangan, S., Li, M., Lewis, M., Shi, W., Althoff, T., Smith, N. A., and Zettlemoyer, L. Scaling expert language models with unsupervised domain discovery. arXiv preprint arXiv:2303.14177, 2023.
- Guu, K., Lee, K., Tung, Z., Pasupat, P., and Chang, M. Retrieval augmented language model pre-training. In

- International conference on machine learning, pp. 3929–3938. PMLR, 2020.
- Han, X., Kumar, S., Tsvetkov, Y., and Ghazvininejad, M. Ssd-2: Scaling and inference-time fusion of diffusion language models. arXiv preprint arXiv:2305.14771, 2023.
- Henshall, W. Big tech companies were investors in smaller ai labs. now they're rivals. https://time.com/6977424/ai-competition-openai-anthropic-microsoft-amazon/, 2024.
- Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E.,
  Cai, T., Rutherford, E., de Las Casas, D., Hendricks,
  L. A., Welbl, J., Clark, A., et al. Training compute-optimal large language models. In *Proceedings of the* 36th International Conference on Neural Information Processing Systems, pp. 30016–30030, 2022.
- Houlsby, N., Giurgiu, A., Jastrzebski, S., Morrone, B., De Laroussilhe, Q., Gesmundo, A., Attariyan, M., and Gelly, S. Parameter-efficient transfer learning for nlp. In *International conference on machine learning*, pp. 2790– 2799. PMLR, 2019.
- Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., and Chen, W. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.
- Hu, Q. J., Bieker, J., Li, X., Jiang, N., Keigwin, B., Ranganath, G., Keutzer, K., and Upadhyay, S. K. Routerbench: A benchmark for multi-llm routing system. *arXiv* preprint arXiv:2403.12031, 2024.
- Huang, C., Liu, Q., Lin, B. Y., Pang, T., Du, C., and Lin, M. Lorahub: Efficient cross-task generalization via dynamic lora composition. *arXiv preprint arXiv:2307.13269*, 2023.
- Hutchins, E. Distributed cognition. *International Encyclopedia of the Social and Behavioral Sciences. Elsevier Science*, 138:1–10, 2000.
- Ilharco, G., Ribeiro, M. T., Wortsman, M., Schmidt, L., Hajishirzi, H., and Farhadi, A. Editing models with task arithmetic. In *The Eleventh International Conference on Learning Representations*, 2023.
- Jang, J., Kim, S., Lin, B. Y., Wang, Y., Hessel, J., Zettle-moyer, L., Hajishirzi, H., Choi, Y., and Ammanabrolu, P. Personalized soups: Personalized large language model alignment via post-hoc parameter merging. arXiv preprint arXiv:2310.11564, 2023.
- Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., and Fung, P. Survey of hallucination in natural language generation. *ACM Computing Surveys*, 55(12):1–38, 2023.

- Jiang, D., Ren, X., and Lin, B. Y. Llm-blender: Ensembling large language models with pairwise ranking and generative fusion. In *Proceedings of the 61st Annual Meeting of* the Association for Computational Linguistics (Volume 1: Long Papers), pp. 14165–14178, 2023a.
- Jiang, Z., Xu, F. F., Gao, L., Sun, Z., Liu, Q., Dwivedi-Yu, J., Yang, Y., Callan, J., and Neubig, G. Active retrieval augmented generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 7969–7992, 2023b.
- Johnson, J. P. Collaboration, peer review and open source software. *Information Economics and Policy*, 18(4):477– 497, 2006.
- Jung, J., Brahman, F., and Choi, Y. Trust or escalate: Llm judges with provable guarantees for human agreement. *arXiv preprint arXiv:2407.18370*, 2024.
- Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., Gray, S., Radford, A., Wu, J., and Amodei, D. Scaling laws for neural language models. arXiv preprint arXiv:2001.08361, 2020.
- Karamolegkou, A., Li, J., Zhou, L., and Søgaard, A. Copyright violations and large language models. In *The 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.
- Kasai, J., Sakaguchi, K., Le Bras, R., Asai, A., Yu, X., Radev, D., Smith, N. A., Choi, Y., Inui, K., et al. Realtime qa: what's the answer right now? *Advances in Neural Information Processing Systems*, 36, 2024.
- Kirk, H. R., Whitefield, A., Röttger, P., Bean, A., Margatina, K., Ciro, J., Mosquera, R., Bartolo, M., Williams, A., He, H., et al. The prism alignment project: What participatory, representative and individualised human feedback reveals about the subjective and multicultural alignment of large language models. arXiv preprint arXiv:2404.16019, 2024.
- Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A. A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017.
- Kumar, S., Balachandran, V., Njoo, L., Anastasopoulos, A., and Tsvetkov, Y. Language generation models can cause harm: So what can we do about it? an actionable survey. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 3299–3321, 2023.

- Kumar, S., Park, C. Y., Tsvetkov, Y., Smith, N. A., and Hajishirzi, H. Compo: Community preferences for language model personalization. *arXiv preprint arXiv:2410.16027*, 2024.
- Lazaridou, A., Kuncoro, A., Gribovskaya, E., Agrawal, D.,
  Liska, A., Terzi, T., Gimenez, M., de Masson d'Autume,
  C., Ruder, S., Yogatama, D., et al. Pitfalls of static
  language modelling. arXiv preprint arXiv:2102.01951,
  2021.
- Leibo, J. Z., Vezhnevets, A. S., Diaz, M., Agapiou, J. P., Cunningham, W. A., Sunehag, P., Haas, J., Koster, R., Duéñez-Guzmán, E. A., Isaac, W. S., et al. A theory of appropriateness with applications to generative artificial intelligence. arXiv preprint arXiv:2412.19010, 2024.
- Leng, S., Zhang, H., Chen, G., Li, X., Lu, S., Miao, C., and Bing, L. Mitigating object hallucinations in large vision-language models through visual contrastive decoding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 13872–13882, June 2024.
- Li, M., Gururangan, S., Dettmers, T., Lewis, M., Althoff, T., Smith, N. A., and Zettlemoyer, L. Branch-train-merge: Embarrassingly parallel training of expert language models. *arXiv preprint arXiv:2208.03306*, 2022.
- Li, X. L., Holtzman, A., Fried, D., Liang, P., Eisner, J., Hashimoto, T., Zettlemoyer, L., and Lewis, M. Contrastive decoding: Open-ended text generation as optimization. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2023.
- Liang, P., Bommasani, R., Lee, T., Tsipras, D., Soylu, D., Yasunaga, M., Zhang, Y., Narayanan, D., Wu, Y., Kumar, A., et al. Holistic evaluation of language models. *Transactions on Machine Learning Research*, 2023a.
- Liang, T., He, Z., Jiao, W., Wang, X., Wang, Y., Wang, R., Yang, Y., Shi, S., and Tu, Z. Encouraging divergent thinking in large language models through multi-agent debate. *arXiv* preprint arXiv:2305.19118, 2023b.
- Lin, Y., Lin, H., Xiong, W., Diao, S., Liu, J., Zhang, J., Pan, R., Wang, H., Hu, W., Zhang, H., et al. Mitigating the alignment tax of rlhf. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 580–606, 2024.
- Liu, A., Sap, M., Lu, X., Swayamdipta, S., Bhagavatula, C., Smith, N. A., and Choi, Y. DExperts: Decoding-time controlled text generation with experts and anti-experts. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the*

- 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), 2021.
- Liu, A., Han, X., Wang, Y., Tsvetkov, Y., Choi, Y., and Smith, N. A. Tuning language models by proxy. In *First Conference on Language Modeling*, 2024.
- Lu, K., Yuan, H., Lin, R., Lin, J., Yuan, Z., Zhou, C., and Zhou, J. Routing to the expert: Efficient rewardguided ensemble of large language models. arXiv preprint arXiv:2311.08692, 2023.
- Luo, Y., Yang, Z., Meng, F., Li, Y., Zhou, J., and Zhang, Y. An empirical study of catastrophic forgetting in large language models during continual fine-tuning. *arXiv* preprint arXiv:2308.08747, 2023.
- Madaan, A., Tandon, N., Gupta, P., Hallinan, S., Gao, L., Wiegreffe, S., Alon, U., Dziri, N., Prabhumoye, S., Yang, Y., et al. Self-refine: Iterative refinement with selffeedback. *Advances in Neural Information Processing Systems*, 36, 2024.
- Mavromatis, C., Karypis, P., and Karypis, G. Pack of LLMs: Model fusion at test-time via perplexity optimization. In *First Conference on Language Modeling*, 2024.
- McCloskey, M. and Cohen, N. J. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pp. 109–165. Elsevier, 1989.
- Meng, K., Bau, D., Andonian, A., and Belinkov, Y. Locating and editing factual associations in GPT. Advances in Neural Information Processing Systems, 36, 2022. arXiv:2202.05262.
- Min, S., Gururangan, S., Wallace, E., Shi, W., Hajishirzi, H., Smith, N. A., and Zettlemoyer, L. Silo language models: Isolating legal risk in a nonparametric datastore. In *The Twelfth International Conference on Learning Representations*, 2024.
- Mireshghallah, N., Kim, H., Zhou, X., Tsvetkov, Y., Sap, M., Shokri, R., and Choi, Y. Can Ilms keep a secret? testing privacy implications of language models via contextual integrity theory. In *The Twelfth International Conference on Learning Representations*, 2024.
- Mitchell, E., Rafailov, R., Sharma, A., Finn, C., and Manning, C. D. An emulator for fine-tuning large language models using small language models. In *The Twelfth International Conference on Learning Representations*, 2024.
- Muqeeth, M., Liu, H., Liu, Y., and Raffel, C. Learning to route among specialized experts for zero-shot generalization. In *Forty-first International Conference on Machine Learning*, 2024.

- Nanda, N., Chan, L., Lieberum, T., Smith, J., and Steinhardt, J. Progress measures for grokking via mechanistic interpretability. In *The Eleventh International Conference on Learning Representations*, 2023.
- Naous, T., Ryan, M. J., Ritter, A., and Xu, W. Having beer after prayer? measuring cultural bias in large language models. *arXiv preprint arXiv:2305.14456*, 2023.
- Ong, I., Almahairi, A., Wu, V., Chiang, W.-L., Wu, T., Gonzalez, J. E., Kadous, M. W., and Stoica, I. Routellm: Learning to route llms with preference data. *arXiv* preprint arXiv:2406.18665, 2024.
- Pei, J., Yang, K., and Klein, D. PREADD: Prefix-adaptive decoding for controlled text generation. In *Findings of the Association for Computational Linguistics: ACL 2023*, 2023.
- Pfeiffer, J., Kamath, A., Rücklé, A., Cho, K., and Gurevych, I. Adapterfusion: Non-destructive task composition for transfer learning. *arXiv preprint arXiv:2005.00247*, 2020.
- Press, O., Zhang, M., Min, S., Schmidt, L., Smith, N. A., and Lewis, M. Measuring and narrowing the compositionality gap in language models. *ArXiv*, abs/2210.03350, 2022.
- Raffel, C. A call to build models like we build open-source software, 2021. Accessed: 2025-01-15.
- Rao, A., Yerukola, A., Shah, V., Reinecke, K., and Sap, M. Normad: A benchmark for measuring the cultural adaptability of large language models. arXiv preprint arXiv:2404.12464, 2024.
- Santurkar, S., Durmus, E., Ladhak, F., Lee, C., Liang, P., and Hashimoto, T. Whose opinions do language models reflect? In *International Conference on Machine Learning*, pp. 29971–30004. PMLR, 2023.
- Sennrich, R., Vamvas, J., and Mohammadshahi, A. Mitigating hallucinations and off-target machine translation with source-contrastive and language-contrastive decoding. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 2: Short Papers)*, 2024.
- Shen, Z., Lang, H., Wang, B., Kim, Y., and Sontag, D. Learning to decode collaboratively with multiple language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2024.
- Shi, R., Chen, Y., Hu, Y., Liu, A., Hajishirzi, H., Smith, N. A., and Du, S. S. Decoding-time language model alignment with multiple objectives. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024a.

- Shi, W., Min, S., Yasunaga, M., Seo, M., James, R., Lewis, M., Zettlemoyer, L., and Yih, W.-t. Replug: Retrieval-augmented black-box language models. *arXiv preprint arXiv:2301.12652*, 2023.
- Shi, W., Han, X., Lewis, M., Tsvetkov, Y., Zettlemoyer, L., and Yih, W.-t. Trusting your evidence: Hallucinate less with context-aware decoding. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 2: Short Papers)*, 2024b.
- Shi, W., Li, R., Zhang, Y., Ziems, C., Horesh, R., de Paula, R. A., Yang, D., et al. Culturebank: An online community-driven knowledge base towards culturally aware language technologies. *arXiv preprint arXiv:2404.15238*, 2024c.
- Shinn, N., Cassano, F., Gopinath, A., Narasimhan, K., and Yao, S. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36, 2024.
- Shnitzer, T., Ou, A., Silva, M., Soule, K., Sun, Y., Solomon, J., Thompson, N., and Yurochkin, M. Large language model routing with benchmark datasets. *arXiv preprint arXiv:2309.15789*, 2023.
- Song, Y., Khanuja, S., Liu, P., Faisal, F., Ostapenko, A., Winata, G., Aji, A., Cahyawijaya, S., Tsvetkov, Y., Anastasopoulos, A., et al. Globalbench: A benchmark for global progress in natural language processing. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 14157–14171, 2023.
- Sorensen, T., Jiang, L., Hwang, J. D., Levine, S., Pyatkin, V., West, P., Dziri, N., Lu, X., Rao, K., Bhagavatula, C., et al. Value kaleidoscope: Engaging ai with pluralistic human values, rights, and duties. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 19937–19947, 2024a.
- Sorensen, T., Moore, J., Fisher, J., Gordon, M. L., Mireshghallah, N., Rytting, C. M., Ye, A., Jiang, L., Lu, X., Dziri, N., et al. Position: A roadmap to pluralistic alignment. In Forty-first International Conference on Machine Learning, 2024b.
- Sprague, Z., Yin, F., Rodriguez, J. D., Jiang, D., Wadhwa, M., Singhal, P., Zhao, X., Ye, X., Mahowald, K., and Durrett, G. To cot or not to cot? chain-of-thought helps mainly on math and symbolic reasoning. arXiv preprint arXiv:2409.12183, 2024.
- Stolfo, A., Belinkov, Y., and Sachan, M. A mechanistic interpretation of arithmetic reasoning in language models using causal mediation analysis. In *Proceedings of*

- the 2023 Conference on Empirical Methods in Natural Language Processing, 2023.
- Stripelis, D., Hu, Z., Zhang, J., Xu, Z., Shah, A. D., Jin, H., Yao, Y., Avestimehr, S., and He, C. Tensoropera router: A multi-model router for efficient llm inference. *arXiv* preprint arXiv:2408.12320, 2024.
- Subramaniam, V., Torralba, A., and Li, S. Debategpt: Fine-tuning large language models with multi-agent debate supervision. 2024.
- Subramaniam, V., Du, Y., Tenenbaum, J. B., Torralba, A., Li, S., and Mordatch, I. Multiagent finetuning: Self improvement with diverse reasoning chains. *arXiv preprint arXiv:2501.05707*, 2025.
- Sukhbaatar, S., Golovneva, O., Sharma, V., Xu, H., Lin, X. V., Rozière, B., Kahn, J., Li, D., Yih, W.-t., Weston, J., et al. Branch-train-mix: Mixing expert llms into a mixture-of-experts llm. arXiv preprint arXiv:2403.07816, 2024
- Sun, T.-X., Liu, X.-Y., Qiu, X.-P., and Huang, X.-J. Paradigm shift in natural language processing. *Machine Intelligence Research*, 19(3):169–183, 2022.
- Suzgun, M., Scales, N., Schärli, N., Gehrmann, S., Tay, Y., Chung, H. W., Chowdhery, A., Le, Q., Chi, E., Zhou, D., et al. Challenging big-bench tasks and whether chain-of-thought can solve them. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 13003–13051, 2023.
- Tambon, F., Nikanjam, A., Khomh, F., and Antoniol, G. Assessing programming task difficulty for efficient evaluation of large language models. arXiv preprint arXiv:2407.21227, 2024.
- Team, G., Anil, R., Borgeaud, S., Alayrac, J.-B., Yu, J., Soricut, R., Schalkwyk, J., Dai, A. M., Hauth, A., Millican, K., et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.
- Team, I. Internlm: A multilingual language model with progressively enhanced capabilities, 2023.
- Vaswani, A. Attention is all you need. *Advances in Neural Information Processing Systems*, 2017.
- Wang, H., Polo, F. M., Sun, Y., Kundu, S., Xing, E., and Yurochkin, M. Fusing models with complementary expertise. In *The Twelfth International Conference on Learning Representations*, 2024.
- Wang, X., Wei, J., Schuurmans, D., Le, Q., Chi, E., Narang, S., Chowdhery, A., and Zhou, D. Self-consistency improves chain of thought reasoning in language models. arXiv preprint arXiv:2203.11171, 2022a.

- Wang, Y., Agarwal, S., Mukherjee, S., Liu, X., Gao, J., Awadallah, A. H., and Gao, J. Adamix: Mixture-ofadaptations for parameter-efficient model tuning, 2022b.
- Wei, B., Shi, W., Huang, Y., Smith, N. A., Zhang, C., Zettle-moyer, L., Li, K., and Henderson, P. Evaluating copyright takedown methods for language models. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024.
- Wu, Q., Bansal, G., Zhang, J., Wu, Y., Li, B., Zhu, E., Jiang, L., Zhang, X., Zhang, S., Liu, J., et al. Autogen: Enabling next-gen llm applications via multi-agent conversation. In ICLR 2024 Workshop on Large Language Model (LLM) Agents, 2024a.
- Wu, X., Huang, S., and Wei, F. Mixture of lora experts. *arXiv preprint arXiv:2404.13628*, 2024b.
- Xiong, K., Ding, X., Cao, Y., Liu, T., and Qin, B. Examining inter-consistency of large language models collaboration: An in-depth analysis via debate. *arXiv preprint arXiv:2305.11595*, 2023.
- Xu, C., Sun, Q., Zheng, K., Geng, X., Zhao, P., Feng, J., Tao, C., and Jiang, D. Wizardlm: Empowering large language models to follow complex instructions. arXiv preprint arXiv:2304.12244, 2023.
- Xu, T., Wu, S., Diao, S., Liu, X., Wang, X., Chen, Y., and Gao, J. Sayself: Teaching llms to express confidence with self-reflective rationales. *arXiv* preprint *arXiv*:2405.20974, 2024.
- Yadav, P., Raffel, C., Muqeeth, M., Caccia, L., Liu, H., Chen, T., Bansal, M., Choshen, L., and Sordoni, A. A survey on model moerging: Recycling and routing among specialized experts for collaborative learning. arXiv preprint arXiv:2408.07057, 2024a.
- Yadav, P., Tam, D., Choshen, L., Raffel, C. A., and Bansal, M. Ties-merging: Resolving interference when merging models. Advances in Neural Information Processing Systems, 36, 2024b.
- Yang, S., Gribovskaya, E., Kassner, N., Geva, M., and Riedel, S. Do large language models latently perform multi-hop reasoning? In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), 2024.
- Yao, Y., Duan, J., Xu, K., Cai, Y., Sun, Z., and Zhang, Y. A survey on large language model (llm) security and privacy: The good, the bad, and the ugly. *High-Confidence Computing*, pp. 100211, 2024.
- Yin, F., Ye, X., and Durrett, G. Lofit: Localized fine-tuning on llm representations. *arXiv preprint arXiv:2406.01563*, 2024.

- Yu, L., Yu, B., Yu, H., Huang, F., and Li, Y. Language models are super mario: Absorbing abilities from homologous models as a free lunch. In *Forty-first International Conference on Machine Learning*, 2024.
- Yue, M., Zhao, J., Zhang, M., Du, L., and Yao, Z. Large language model cascades with mixture of thoughts representations for cost-efficient reasoning. *arXiv* preprint *arXiv*:2310.03094, 2023.
- Zhang, K., Wang, J., Hua, E., Qi, B., Ding, N., and Zhou, B. Cogenesis: A framework collaborating large and small language models for secure context-aware instruction following. *arXiv preprint arXiv:2403.03129*, 2024.
- Zhang, S., Dong, L., Li, X., Zhang, S., Sun, X., Wang, S., Li, J., Hu, R., Zhang, T., Wu, F., et al. Instruction tuning for large language models: A survey. *arXiv preprint arXiv:2308.10792*, 2023.
- Zhao, J., Plaza-del Arco, F. M., and Curry, A. C. Language model council: Benchmarking foundation models on highly subjective tasks by consensus. *arXiv* preprint *arXiv*:2406.08598, 2024a.
- Zhao, Q., Wang, J., Zhang, Y., Jin, Y., Zhu, K., Chen, H., and Xie, X. Competeai: Understanding the competition dynamics of large language model-based agents. In *Forty-first International Conference on Machine Learning*, 2024b.